Allocating AUVs for Mine Map Development in MCM

Andrew Rajala
Center for Intelligent Systems Research, University of Idaho, Moscow, ID 83844-1024
Dean Edwards
Center for Intelligent Systems Research, University of Idaho, Moscow, ID 83844-1024

Abstract – *When cooperating Autonomous Underwater Vehicles (AUVs) are used for large area mine countermeasures (MCM), it is important for each vehicle to have a map of the entire search area. If each AUV only has a map of the area it has covered, that information will be lost if the vehicle is lost. To build a complete coverage map in each AUV, a scheduling algorithm, language, and logic were developed. The scheduling algorithm is an optimized fuzzy logic system that assigns the formations AUVs to inspect mine like objects (MLOs), while keeping the formation together. The language was developed to communicate the information needed to build a map and deal with the limited bandwidth of underwater communication. The vehicle logic takes the communicated information and compiles it into a map. The fuzzy logic scheduling algorithm significantly improved how the formation allocated its resources and the map generated in each of the vehicles closely matched the actual map*

I. INTRODUCTION

Fleets of cooperating AUVs are being investigated for underwater MCM missions, which is the location, classification, and neutralization of underwater mines. The initial task of locating the MLOs is a mapping operation. Typically when AUVs are used for mapping, the vehicles act independently, and the information is compiled after the mission. When cooperating AUVs are used, the formation must achieve complete coverage while vehicles are lost. Since it is unknown when an AUV will be lost, the information needs to be communicated as it is found or the information will be lost with the vehicle. Each AUV needs a complete map because any vehicle can become lost.

Scanned, un-scanned, and dangerous areas should also be stored in the map. Along with knowing where the mines are, it is important to know what areas have been searched. Of the scanned areas, some will be searched better then others and this should be stored in the map for path planning. There are a number of things that can cause an AUV to be lost: equipment malfunction, counter countermeasure (CCM), debris, seaweed, etc. Areas that are dangerous for AUVs need to be mark in the map. For this paper, the language and logic for communicating the information and building the map in each vehicle was developed.

The second step of classifying the objects is a target acquisition problem. When an AUV passes through an area, it can only detect a MLO. Another AUV needs to further inspect and classify it as a mine or obstacle. In shallow water, this is done with crawlers that can stop at the mine. Another approach is to have the subs classify the MLO by inspecting it from different angles. In this paper, a fuzzy logic scheduling algorithms that assigns AUVs to inspect MLOs was developed. The MLOs are inspected as they are found.

This work was supported by the Office of Naval Research (ONR) under award "Developing Fleets of Autonomous Vehicles" No. N00014-05-1-0674.

II. BACKGROUND

The use of multiple AUVs for MCM operations is being explored to meet the U.S. Navy's large area coverage requirements (e.g., 30km x 30km in a week). For complete coverage, AUVs that cooperate and deal with problems during the mission could dramatically improve the performance. Some of our previous work includes replacing a lost vehicle [1] and dealing with lost communication [2]. When an AUV is lost, the remaining vehicles need to collaborate to cover the lost vehicle's remaining search area. It becomes difficult to determine when a vehicle is lost if lost communications are introduced. In those works, a logic and language for communicating information between the AUVs was developed.

For cooperation, the AUVs need to share information and make requests, which requires a communication system and a common language. There has been work done on AUV languages and include Conceptual Language for AUVs (COLA) [3] and Common Control Language (CCL) [4]. Existing AUV languages are generally command and control languages that are designed to be short for the limited bandwidth of underwater communication. COLA explored some natural language concepts to deal with the high error rates of underwater communication.

The AUVs need internal logic and a control structure. The logic processes the messages and makes decisions, while the control structure determines the conversion policy. In our previous work, a centralized control system was used for simplicity. The conversation policy had the formation's leader sending commands and the other vehicles broadcasting information. The formation, in Fig. 1, performed a lawnmower search pattern with a leader, swimmers, and followers. The leader makes the formations decisions, the swimmers fill out the formation, and the followers are used for replacing lost vehicles and further inspecting MLOs.

Report Documentation Page

Form Approved
OMB No. 0704-0188

1. REPORT DATE **2006**	2. REPORT TYPE	3. DATES COVERED **00-00-2006 to 00-00-2006**
4. TITLE AND SUBTITLE **Allocating AUVs for Mine Map Development in MCM**		5a. CONTRACT NUMBER
		5b. GRANT NUMBER
		5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S)		5d. PROJECT NUMBER
		5e. TASK NUMBER
		5f. WORK UNIT NUMBER
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) **University of Idaho,Center for Intelligent Systems Research,Moscow,ID,83844**		8. PERFORMING ORGANIZATION REPORT NUMBER
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)		10. SPONSOR/MONITOR'S ACRONYM(S)
		11. SPONSOR/MONITOR'S REPORT NUMBER(S)
12. DISTRIBUTION/AVAILABILITY STATEMENT **Approved for public release; distribution unlimited**		
13. SUPPLEMENTARY NOTES **The original document contains color images.**		
14. ABSTRACT		
15. SUBJECT TERMS		

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT **unclassified**	b. ABSTRACT **unclassified**	c. THIS PAGE **unclassified**		**8**	

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std Z39-18

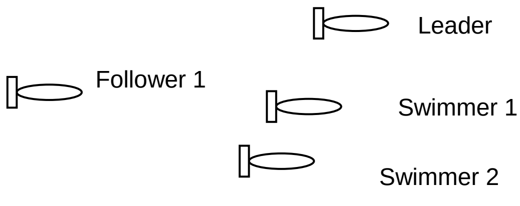

Fig. 1. AUV Formation

In our work, each AUV was given the same logic, a formation ID, and a vehicle number. Because all AUVs had the same logic, any AUV could to take on any role in the formation, which is determined by the formation ID (see Fig. 2). The vehicle number (i.e. the vehicle's serial number) stays constant, and is used to refer to the vehicle. The logic was expanded so each AUV kept a complete map and the followers could inspect and classify MLOs.

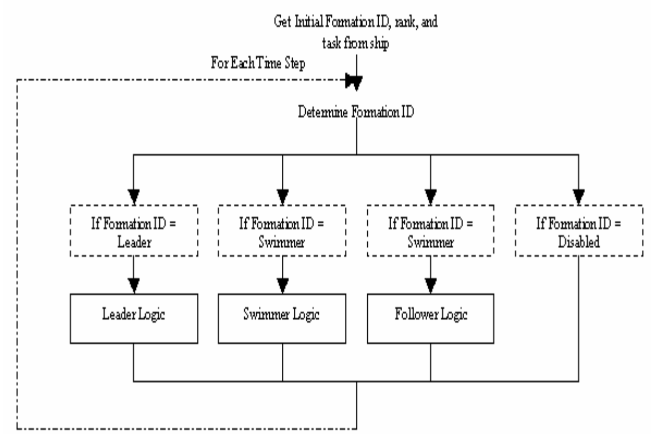

Fig. 2. General Vehicle Logic

Mapping with AUVs is nothing new but has typically been for environmental sampling or ocean topography. These operations are typically done with a single vehicle or multiple vehicles acting independently. Much of the information collected is sonar data, where there is too much information to be communicated acoustically. Therefore, the information is compiled into a complete map when the AUVs return [5].

Underwater crawlers, vehicles that are on the ocean bottom, have been used to classify MLOs or target acquisition. Cook [6] explored algorithms for acquiring targets with crawlers that communicate with each other and took into account the limited bandwidth of underwater communication and high vehicle attrition rate. He explored several algorithms, and the search time was decreased as the vehicles knew more information about each target's classification status. In these simulations the MLOs were known at the start of the mission.

Welling [7] tried another approach with subs and crawlers. In this situation, the sub would do a sweep of the area, locate the mines, and communicate that information to the crawlers. The crawlers used fuzzy logic to determine who would inspect the mines. For large numbers of mines, the fuzzy logic was optimized to decrease the time it took to inspect all the reported mine locations.

III. ENVIRNMONMENT AND SIMULATION

Autonomous Littoral Warfare Systems Evaluator- Monte Carlo (ALWSE-MC) was used to simulate the environment. ALWSE-MC is developed and maintained by the Naval Surface Warfare Center in Panama City and is a kinematics, statistical AUV mission simulator. The AUVs are simulated by point masses with defined sensor packages. The developed logic controls the AUV's actions and is incorporated through a behavior module that executes Matlab scripts.

Communication is done in ALWSE-MC with an internal communication module. The WHOI acoustic micro modem model was used because it is the acoustic modem being used on the University of Idaho fleet of low cost AUVs. Based on the message size, the module calculates the transmission and travel time and waits the calculated time before putting the message into the other vehicle's inbox. Several assumptions were made about the communications. (1) The communication is perfect (i.e., no errors or lost communication). (2) Only one AUV can talk at a time. (3) The AUVs have a spherical transducer so that all vehicles can here all the messages. A 32-byte message packet was assumed because that is currently the smallest message packet available on the WHOI micro-modem even though the language is design to use less. ALWSE-MC calculated 3.2s for transmission and .04s for travel; therefore, the AUVs communicate on five seconds intervals due to the simulation time step in ALWSE, and the time between communications for a single vehicle is five seconds times the total number of vehicles

IV. MAP

Due to the limited bandwidth of underwater communication, the AUVs are limited on the amount of data they can transmit. Therefore, the AUVs only transmit the critical information and infer everything else. Six types of information were chosen to be stored in the map: un-scanned areas, scanned areas, unknown objects, non-lethal objects, lethal objects, and areas dangerous for AUVs. The map was divided into cells and each cell was assigned a number depending on what is in the cell; the numbers for each kind of information is listed in Table 1. Cells were chosen because AUVs do not have to transmit the whole mine location or have all the vehicles with the same names for the mines. Instead, AUVs can refer to the cell the mine is in. Some accuracy is lost when the map is divided into cells. Given the error in the vehicle navigation, this is not important.

TABLE 1
AUV MAP CELL VALUES

Value	Item
0	Un-scanned
0-1	Scanned and clear
2	Unknown obstacle
3	Non-lethal object
4	Lethal Object
5	Dangerous Areas

It is important to know what areas have not been scanned because they are unknown and dangerous. If the formation tracks what areas have been missed, it can assign AUVs to cover those areas or personnel can avoid them. In the map, all the cells initially start as being un-scanned.

A cell becomes scanned when an AUV passes by it. Along with knowing which cells have been search, it is important to known the probability that the area is clear. This depends on the AUVs' sensors and vehicles' paths. With areas covered by more then one AUV, followers diverging from the normal path, and vehicles becoming lost, certain areas will be covered better then others. How well they have been covered can be determined from the probability charts of the sensors. The sensor on the AUVs, in the ALWSE-MC simulation, was a side-scan sonar with the sensor-mine relationship shown in Fig. 3, but is not the true probability function for the sensor.

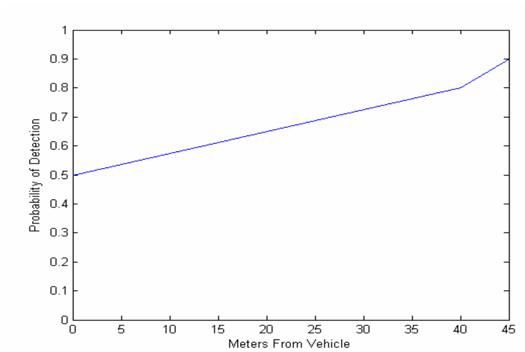

Fig. 3. Sensor-Mine Relationship in ALWSE_MC

When two vehicles pass over the same area, it can be treated as two independent events. If we assumed there is a mine in the cell, we can find the probability that at least one of the vehicles detected the mine from (1); this is the probability that the cell is cleared and what is stored in the map.

$$\% \text{ Detection} = 1 - \% \text{ No Detection} \quad (1)$$

The % No Detection can be found by treating the passes as independent events and is in (2), where the probability of either vehicle not detecting the mine are multiplied together.

$$\%\text{No Detection} = \%\text{No Detection V1x } \%\text{No Detection V2} \quad (2)$$

Unknown object, non-lethal object, and lethal object have to do with finding and classifying the MLOs. When an AUV detects a mine with side scan sonar, it can only detect a MLO and give a probability of it being a mine. This is done with algorithms based off the fact that manmade objects tend to have a regular shape [8]. Another AUV needs to further inspect and classify the object. For the simulations, the first AUV classifies the MLO as an unknown object. The followers classify the MLO, by inspecting it from different angles. Ideally each obstacle would be given a probability of being a mine, but ALWSE-MC has a binary object classification so each object is classified as either a lethal or non-lethal object.

The last piece of information stored in the map is the dangerous areas. If an AUV is lost in an area, the formation does not want to send more vehicles through the same area; therefore, the AUVs mark the area as dangerous, so they can avoid it in the future. In order to mark the correct cells as dangerous, the AUVs will need to know the lost vehicle's location, and the language was modified to accomplish this.

V. COMMON LANGUAGE

The language we had previously developed [1,2] was further expanded to communicate the information needed for the map. The major additions were for the MLOs and determining where the AUVs had been. For the mine locations, Unknown Object, Inspect Unknown Object, Object is a Mine, and Object is a Rock were all added to the language. These allowed AUVs to report an object to the other vehicles, permits the leader to assign a follower to inspect an unknown object, and provides a means for the follower to classify an object.

The AUVs need to known where each vehicle has been in order to determine what areas have been scanned and what areas are dangerous. Since it is unrealistic to broadcast the entire vehicle's path, Vehicle In Cell was added to the language. If an AUV has nothing to transmit, it reports what cell it is in. This way, the other vehicles have an estimate of the vehicle's path. The whole language is listed below where the messages are given syntax and only a certain list of words can go in each slot. Message parsing was built in the language for further introducing natural language error correction into the simulations.

Messages are broken into six parts

1. Transmitting Vehicle Number
2. Transmitting Vehicle Status
3. Message Type Indicator
4. Intended AUV's Vehicle Number
5. Message
6. Additional Information

1. Transmitting Vehicle Number: Vehicle serial number
    - 1-10

2. Transmitting Vehicle Status: Vehicle's formation ID
    - Leader
    - Swimmer 1-10

- Follower 1-10
- Deactivated

3. Message Type: Indicates the type of message to come, used for sorting messages and error detection.
   - Request
   - Information

4. Intended AUV's Vehicle Number: Vehicle number of the intended recipient of the message. If a zero is used, then the message is intended for all the AUVs in the formation.
   - 0-10

5. Message: Can be a request or information.
   - Requests: Replace Swimmer
Reconfigure Pattern
Become Follower
Become Swimmer
Request Vehicle Position
Inspect Unknown Object
   - Information: Vehicle is in Swimmer
Vehicle is in Follower
Vehicle is Disabled
Unknown Object
Object is a Rock
Object is a Mine
Vehicle is at Cell

6. Additional Information: This slot is for information tied to the message. It identifies which AUV is to be replaced or the cell location of a mine or vehicle.
   - 1-10
   - (1-200,1-200)

Examples

The first part is how the message appears to the vehicle (Italics) and the second part is how the message would be read by a person.

"3" "S1" "0" "UnkObj" "175 35"
Vehicle 3 is in the Swimmer 1 position. This message is for every vehicle. There is an unknown object in cell (175,035).

"1" "L" "6" "InsObj" "175 035"
Vehicle 1 is in the Leader position. Vehicle 6 inspect the unknown object in cell (175, 35).

"5" "F1" "0" "ObjMin" "175 035"
Vehicle 5 is in the Follower 1 position. This message is for every vehicle. The object in cell (175, 35) is a mine.

VI. OBJECT CLASSIFICATION

A. Closest Follower

Two scheduling methods, for assigning followers to inspect MLO, were compared. The first was the closest follower method. When a MLO was reported to the leader, it assigns the closest follower to inspect the MLO. The last position update from each follower is used to determine the closest follower.

B. Fuzzy System

The second scheduling method was a fuzzy logic based system. When a MLO is reported to the leader, it uses fuzzy logic to determine whether it should wait to assign a follower and which follower to assign. The fuzzy system was designed to keep the formation together and evenly distribute the mines. The approach is based off the work by Welling [7], but modified for subs in a lawnmower search pattern. There are three fuzzy sets: Availability, Behind, and Lane.

The Availability fuzzy set is based on the number of MLOs the follower has been assigned to inspect. The Availability is to prevent one of the followers from being overloaded with MLOs. The corresponding membership function is shown in Fig. 4.

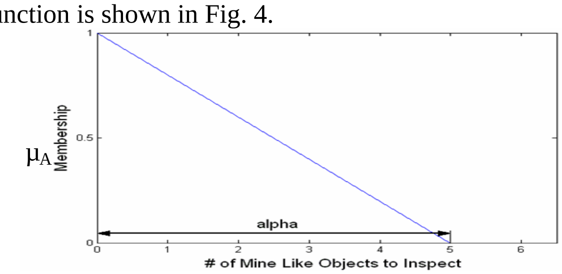

Fig. 4. Availability Membership Function

The Behind membership function is shown in Fig. 5. The input is the MLO's distance behind the leader. It gives MLOs further behind the formation higher priority and keeps the followers behind the formation.

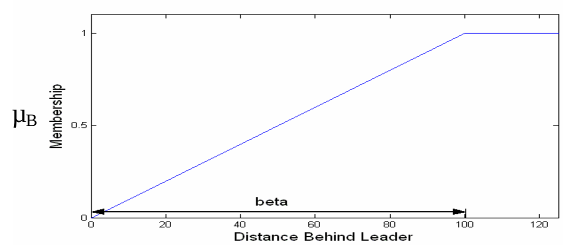

Fig. 5. Behind Membership Function

The Lane membership function for two followers is shown in Fig. 6. The input is the distance from the leader looking at Fig. 1, towards the swimmers. Lane gives higher priority to objects in the follower's lane and to objects in areas the formation has already searched and lower priority to objects in areas the formation will search in the future. As gamma goes to one, followers will not go into the other lane, and as gamma goes to .5, followers have equal membership in both lanes.

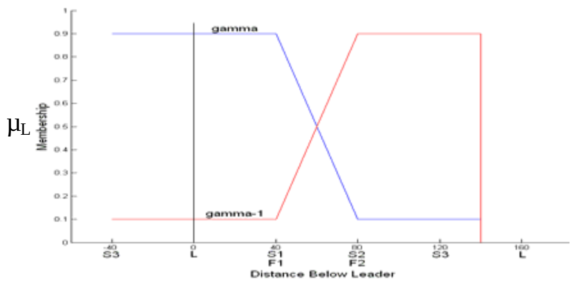

Fig. 6. Lane Membership Function

C. Output

The final decision is based off the total membership. In assigning followers to inspect MLOs, the leader has to deal with the limited bandwidth and time between communications; the leader can have several MLOs that need to be inspected. Therefore, the leader must determine what follower/MLO pair is going to transmit on its turn. The leader selects the follower/MLO pair with the highest total membership above zero. The total membership is calculated by (3). The three memberships are multiplied together so that if one membership is low it drives the total membership down.

$$\mu_{T_{V,M}} = \mu_{A_{V,M}} \times \mu_{B_{V,M}} \times \mu_{L_{V,M}} \qquad (3)$$

(3) produces a matrix, and the highest value is selected. If none of the values are above zero, the leader waits until one of the total memberships is above zero.

VII. RESULTS

A. Optimization

The fuzzy system was optimized to keep the formation together, while inspecting every detected MLO. The performance index is shown in (4) and totals how far the follower is from the formation for each time step.

$$PI = \sum_t Dist + 10^6 \times UnInsp\_Object \qquad (4)$$

In (4), $Dist$ is the distance from each follower's current location to where it should be in the formation and is summed up for each time step. $UnInsp\_Object$ is the number of objects found but not assigned to any vehicle. This is a penalty to prevent MLO from not being inspected. Without it, the performance index would go to zero if the leader never assigned the followers to inspect the MLOs.

The simplex method was used to optimize the fuzzy system, and the results are shown in Fig. 7. Each iteration was run through 50 random minefields. As you can see from Fig. 7, the performance index quickly decreases to about 1.9 x 10^5 and the standard deviation continues to decrease. The decrease in the standard deviation means that the MLOs where more evenly distributed among the followers.

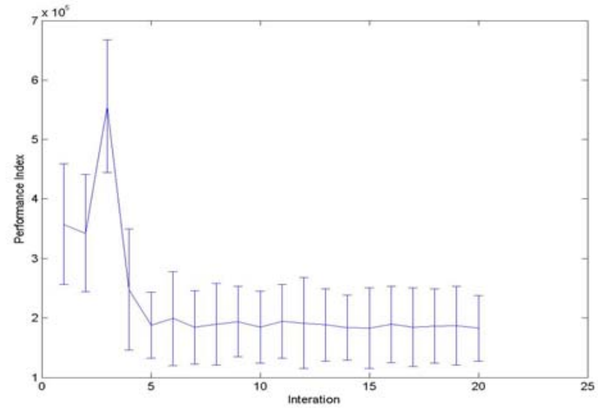

Fig. 7. Results of the optimization

B. Comparision

The closest follower and fuzzy logic system are compared in Table 2; the performance index and standard deviation for 50 runs is shown for the closet follower and optimized fuzzy system. The optimzed fuzzy system is over 25% less than the closet follower method.

TABLE 2
Closest Follower and Optimized Fuzzy System

Method	Performance Index
Closest Follower	2.52x10^5±7.6x10^4
Optimized Fuzzy System (α=6.4, β=73, and γ=.86)	1.82x10^5±5.5x10^4

Fig. 8 shows the closest follower method, and Fig 9 shows the optimized fuzzy logic system through the same minefield. In the closest follower method, Fig. 8, the possible MLOs are not found in an optimal order, and the leader assigns a follower to inspect the MLOs as they are found. Follower two diverges into areas that the formation will inspect in the future; this causes follower two to fall significantly behind the formation, which can be seen by the large cuts it makes to catch up.

The optimized fuzzy logic system, Fig. 9, reduces the problems discussed above. The followers stay with the formation and do not venture into areas the formation will be inspecting on the next pass.

C. Maps

For the vehicle's map, the formation was run through a minefield with mines, rocks, and a CCM. The map created by the leader, Fig. 11, closely matches the true map, Fig. 10. The true map shows the mines, rocks, CCM, and the true coverage of each cell. The actual coverage of each cell was determined from the mine-sensor relationship, shown in Fig. 3, and the true paths of the AUVs. The leader's map was compiled during the mission with information communicated from the other AUVs. The mines, rocks, and dangerous areas are properly identified. How well each cell has been covered does not perfectly match the actual coverage and the un-scanned cells don't exactly match.

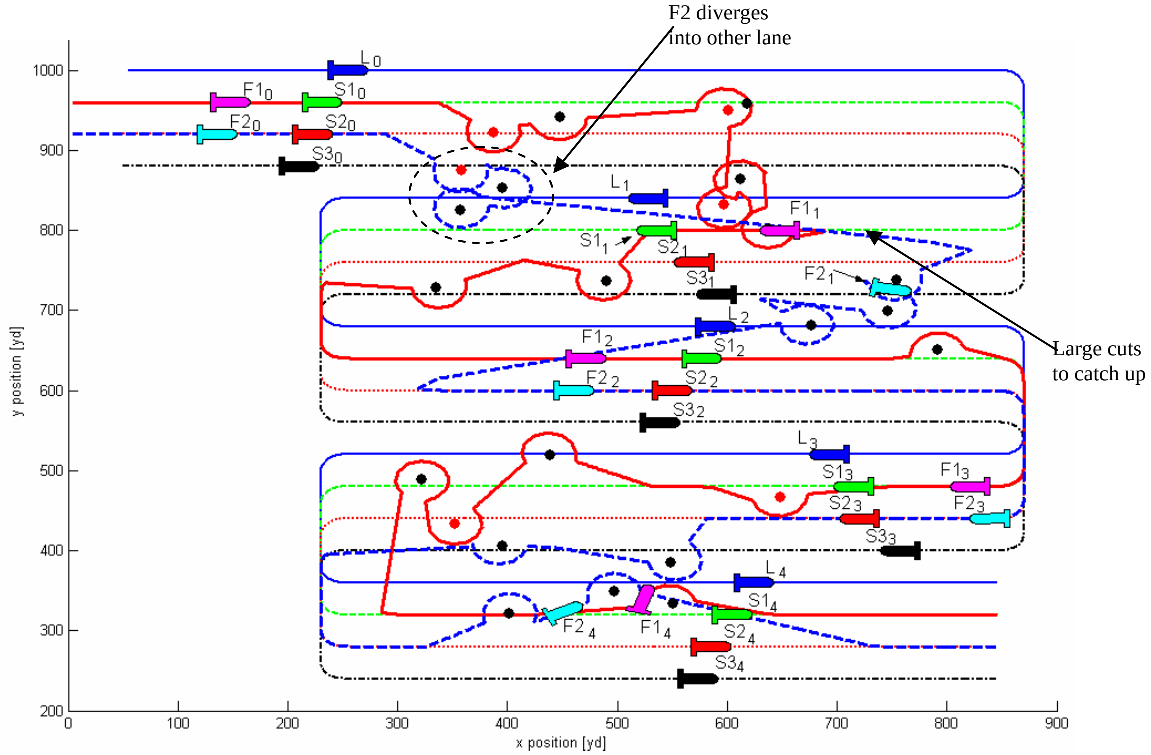

Fig. 8. The closest follower method: the leader assigns the closest follower to inspect the MLOs as the swimmers find them. Follower two diverges into the next lane, back tracks, and makes large cuts to catch up to the formation.

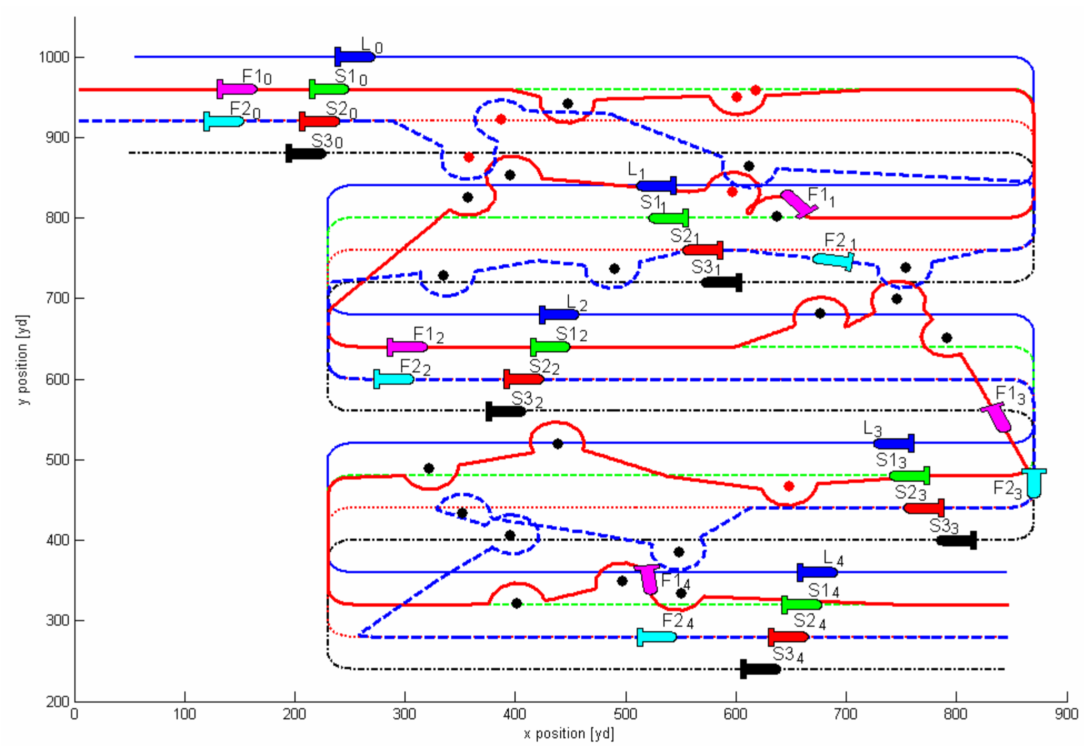

Fig. 9. Optimized fuzzy logic system for assigning the followers to inspect the MLOs.

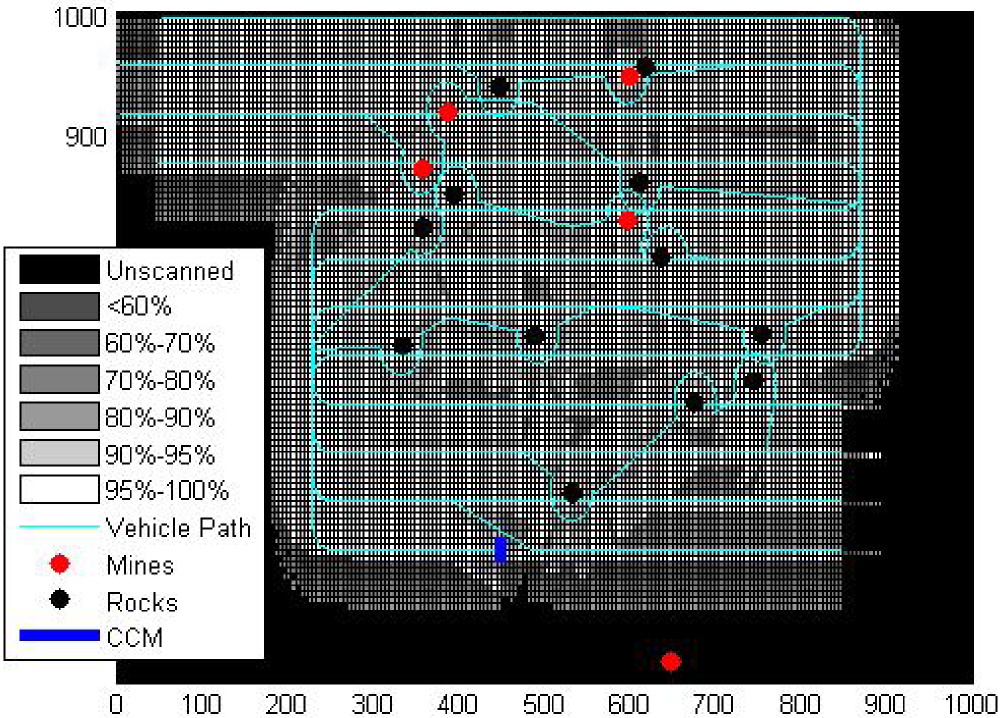

Fig. 10. Actual map showing which areas had been scanned, how well they have been scanned, the vehicle paths, mines, rocks and CCM.

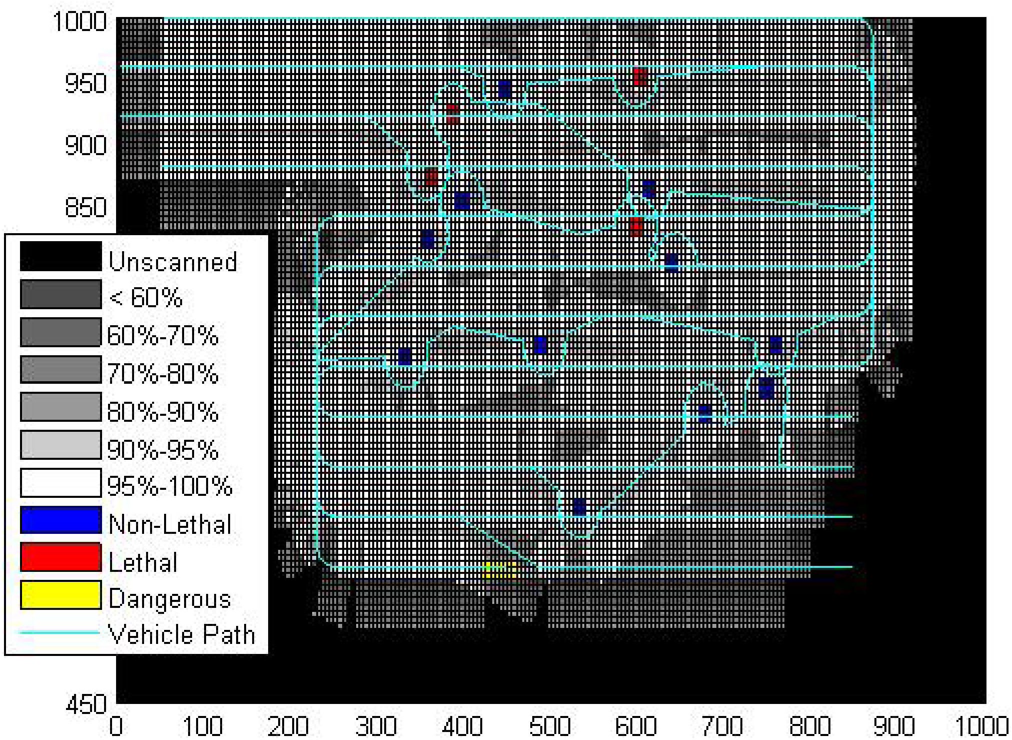

Fig. 11. The map created in the leader from the other AUV's communications shown which areas had been scanned, how well they were scanned, non-lethal objects, lethal objects, dangerous areas, and the vehicle paths.

VIII. CONCLUSION

Resource allocation is an important part of cooperative behavior of AUVs. The leader must assign the resources effectively or the cooperative behavior will be hindered by overloading certain AUVs with tasks, having AUVs fall out of communication range, and draining some AUV's energy more than others. The fuzzy logic scheduling algorithm reduced these problems by keeping the formation together and evenly distributing the MLOs. In the optimized fuzzy system, the followers still need to make some cuts to catch up to the formation, but the cuts are smaller and more spread out. The optimized fuzzy variables (α, β, γ) depend on the sensors. A more accurate model is needed to determine the true parameters, but this shows that the fuzzy logic system significantly improved the performance.

In MCM operations, it is important for each vehicle to keep a complete coverage map. Without this map, the information will be lost if the vehicle is lost. The map developed in the leader, Fig 11, contains information needed to obtain complete coverage. The mines and rocks are properly identified, but that truly depends on the sensors and algorithms for classifying MLOs used on the AUVs. A larger then needed area is marked as dangerous because the leader does not know the exact location of the lost vehicle. Therefore, the leader marks the area between the lost vehicle's last known position and where it should have been when it was declared lost. The biggest differences in the maps are the un-scanned cells and how well each cell has been scanned. These differences are because the leader does not know the exact path of the other AUVs; it is assuming a straight line path between the position updates. While the un-scanned cells do not exactly match, the leader's map has the general area correct. This is enough for the leader or personnel to know that the area needs to be researched or avoided. For each cell's coverage, the general areas of high covered match the actual map, which is valuable if a path is needed through the area. The difficulty of developing a complete map in each of the vehicles is communicating the information, which was dealt with in the developed language and vehicle logic.

REFERENCE

[1] Rajala A., Edwards D., "Vehicle Replacement in AUV Formation." *Proceedings of the 14th International Symposium of Unmanned Untethered Submersible Technology*, August 2005.

[2] Rajala A., Edwards D., O'Rourke M., "Collaborative Behavior for Vehicle Replacement in AUV formations", *Proceedings of the 2005 ASME-IMECE*, Orlando, Florida, November 5-11, 2005.

[3] Turner E., Chappell S., Valcourt S., 1994, "COLA: A Language to Support Communication between Multiple Cooperating Vehicles," *IEEE*, 0-7803-1808-0, pp.309-316.

[4] Phoha S., Ortego T., Fulbright R., Schmiedekamp M., "CCL: A Common Control Language for Autonomous Networks of Unmanned Underwater Vehicles," *Autonomous Robot, 2003*.

[5] Schmidt H., Leonard J., Edwards J., Liu T., "Sub-Seabed Mapping AUV-Based Multi-Static Acoustic Sensing and Adaptive Control," *International Congress on the Application of Recent Advances in Underwater Detection and Surveying Techniques to Underwater Archeology*, Bordrum, Turkey, May 3-7, 2004

[6] Cook, B., Marthaler, D., Topaz, C., Bertozzi, A., Kemp, M., "Fractional Bandwidth Reacquisition Algorithms for VSWMCM," Multirobot systems: from swarms to intelligent autonoma, Volume II, 2003, Kluwer Acad. Publishers, Dordecht, A.C. Schultz et. al. eds. 77-86.

[7] Welling, D. and D. Edwards. 2005. "Multiple Autonomous Underwater Crawler Control for Mine Reacquisition." *Proceedings of the 2005 ASME-IMECE*, Orlando, Florida, November 5-11, 2005.

[8] S. Reed, Y. Petillot, and J. Bell, "A Model Approach to Mine Detection and Classification in Sidescan Sonar," in *OCEANS 2003*. Proceedings, vol. III, pp. 1402-1407, Sept 2003.